Synopsis for Registration as Research Student
For
Doctoral Degree
On
Deep Learning for Agriculture Applications

By

Sandesh Pralhad Bhagat
Research Scholar

Supervisors

Dr. M. B. Kokare

Department of Electronics and Telecommunication Engineering
Shri Guru Gobind Singhji Institute of Engineering and Technology,
Nanded-431606 (MS.) India.

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1. Abstract

With being rapid increasing population in worldwide, the need for satisfactory level of crop production with decreased amount of agricultural lands. Machine vision would ensure the increase of crop production by using an automated, non-destructive and cost-effective technique. In last few years, remarkable results have been achieved in different sectors of agriculture. These achievements are integrated with machine learning techniques on machine vision approach that cope with colour, shape, texture and spectral analysis from the image of objects.

Despite having many applications of different machine learning techniques, this review only described the statistical machine learning technologies with machine vision systems in agriculture due to broad area of machine learning applications. Two types of statistical machine learning techniques such as supervised and unsupervised learning have been utilized for agriculture. This paper comprehensively surveyed current application of statistical machine learning techniques in machine vision systems, analyses each technique potential for specific application and represents an overview of instructive examples in different agricultural areas. Suggestions of specific statistical machine learning technique for specific purpose and limitations of each technique are also given. Future trends of statistical machine learning technology applications are discussed.

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Keywords: Deep Learning, Precision Agriculture, Smart Farming, Convolution Neural Network, Plant disease identification, plant phenotyping.

2. Introduction and Motivation

The world's population is assumed to be nearly 10 billion by 2050, boosting agricultural order-in a situation of humble financial development by somewhere in the range of 50% contrasted with 2013 (FAO, 2017) and the continuing decline of arable land for agricultural cultivation. At present, about 37.7% of total land surface is used for crop production (World Bank, 2015). People would require raising overall food production by around 70 percent between 2005/07 and 2050 (FAO, 2009). However, farmers in worldwide will need to ensure the projected amount of crop production, by enhancing productivity on existing agricultural cultivable land by the adoption of precision Agriculture or smart farming (Elferink and Schierhorn, 2016). at the same time maintaining availability and high nutritional quality across the globe, protecting the natural ecosystems by using sustainable farming procedures.

The Precision Agriculture (PA) or Smart farming is the new Agricultural Evolution. Improving crop yield production and quality while reducing operating costs and environmental pollution is a key goal in precision agriculture. Precision agriculture can harness the power of science and technology to improve crop productivity and also involves minimizing of the pesticides and diseases through precisely targeting amount of pesticides required. As precision farming is shifting to the new techniques from the traditional methods, it has emerged as an improvement in various sectors of agriculture. The sole purpose behind Precision farming is to get real time data to increase crops productivity and maintain the quality of crops. However, agriculture is facing tremendous challenges including the changing climate, severe short fall of arable land and water resources, as well as the threat from diseases, pests and weeds (Lee et al., 2010). The deep learning techniques are applied to precision agriculture and its approach in crops protection field is good enough to increase the crops growth. We use deep learning-based algorithms to solve these challenges mainly plant stress phenotyping or diseases detection and weed detection.

The problem of efficient plant disease protection is closely related to the problems of sustainable agriculture and climate change (Garrett et al., 2006). Research results indicate that climate change can alter stages and rates of pathogen development; it can also modify host resistance, which leads to physiological changes of host-pathogen interactions (Coakley et al., 1999) and (Chakraborty et al., 2000). The situation is further complicated by the fact that, today, diseases are transferred globally more easily than ever before. New diseases can occur in places where they were previously unidentified and, inherently, where there is no local expertise to combat them (Tatem et al., 1999) and (Van der Zwet et al., 2000). Inexperienced pesticide usage can cause the development of long-term resistance of the pathogens, severely reducing the ability to fight back. Timely and accurate diagnosis of plant diseases is one of the pillars of precision agriculture (Miller et al., 2010). It is crucial to prevent unnecessary waste of financial and other resources, thus achieving healthier production, by addressing the long-term pathogen resistance

development problem and mitigating the negative effects of climate change. In this changing environment, appropriate and timely disease identification including early prevention has never been more important. There are several ways to detect plant pathologies. Some diseases do not have any visible symptoms, or the effect becomes noticeable too late to act, and in those situations, a sophisticated analysis is obligatory. However, most diseases generate some kind of manifestation in the visible spectrum, so the naked eye examination of a trained professional is the prime technique adopted in practice for plant disease detection. In order to achieve accurate plant disease diagnostics a plant pathologist should possess good observation skills so that one can identify characteristic symptoms (Riley et al., 2002). Variations in symptoms indicated by diseased plants may lead to an improper diagnosis since amateur gardeners and hobbyists could have more difficulties determining it than a professional plant pathologist. An automated system designed to help identify plant diseases by the plant's appearance and visual symptoms could be of great help to amateurs in the gardening process and also trained professionals as a verification system in disease diagnostics. Advances in computer vision present an opportunity to expand and enhance the practice of precise plant protection and extend the market of computer vision applications in the field of precision agriculture.

The problem of weed control solve by automatically detect and classify weeds in images from fields. This is the first step of an automated precision weed control system. Automatic detection of weeds is a well-established research area with a big potential in precision agriculture. Nevertheless, there has been limited success in the classification of multiple weed species under natural field conditions, including overlapping plants. With recent advances in convolutional neural networks, this dissertation demonstrates methods that can classify weeds in field-images that are collected using consumer cameras.

Controlling weeds is an important task in agriculture because weeds compete with crops in the field, contributing to a lower crop yield. The overall loss of yield due to weeds is estimated to be more than 30% for wheat, rice, maize, potatoes, soybeans, and cotton if weeds are not controlled (Oerke, 2006). today, the majority of agricultural land is cultivated conventionally. Weeds are controlled chemically by applying herbicides to the field or Weeds can also be controlled mechanically Conventional chemical weeding sprays herbicides uniformly to the total field, regardless of the presence of weeds or not, resulting in high cost on herbicides. Furthermore, over use of herbicides in agriculture has caused catastrophic environmental pollution problems (Rodrigo et al., 2014). To counteract these issues, many European countries started to restrict the use of herbicides in agriculture (Hamudaetal.,2016). Proposed system will detect accurate location of weed and crop using deep learning algorithms and optimal herbicide dosage at a given to the weed location only. thus, we achieve saving of herbicide and reduce environmental damage due to herbicide.

3. Literature Survey

Plant Diseases Detection:

(Ferentinos et al., 2018) has used convolutional neural network models were developed to perform plant disease detection and diagnosis using simple leaves images of healthy and diseased plants, through deep learning methodologies. use a database of 87,848 images, containing 25 different plants in a set of 58 distinct classes of [plant, disease] combinations, including healthy plants.

(Sladojevic et al., 2016) has downloaded the dataset from the Internet, searched by disease and plant name on various sources in different languages, able to recognize 13 different types of plant diseases using fine-tuned CNN model with 96.30% accuracy.

(Lu, Yang, et al, 2017) has created his own dataset with agriculture experts and implemented deep learning-based model for detection of diseases and pests in rice plants can help to apply an early treatment reducing economic losses substantially with 99.69% accuracy using DenseNet169

(Fuentes et al., 2017) has created own dataset for real-time tomato plant diseases and pests recognition with Faster R-CNN with VGG-16 shows better recognition results.

(Zhang et al., 2018) has improve the identification accuracy of maize leaf diseases by reducing the number of network parameters, GoogLeNet and Cifar10 models are proposed for leaf disease recognition with 98.9% and 98.6% accuracy respectively.

(Mohanty et al., 2016) has used publicly available dataset Plantvillage consist of 54,306 images with 38 different classes use AlexNet and GoogLeNet achieve 99.35% accuracy.

(Lin et al., 2019) has done schematic segmentation for Powdery mildew disease using U-NET architecture achieving an average pixel accuracy of 96.08% accuracy also create cucumber leaves dataset.

In literature we found that lack of publicly available dataset many authors also created their own dataset thus we plan to create pigeon pea dataset with the help of agriculture experts. we will use deep learning based state of art models to achieve robust plant diseases detection and diagnosis system.

Weed Detection:

(Sa et al., 2017) has done Semantic Segmentation of weed, crop and Background using Multispectral Images captured from UAV, developed encoder-decoder cascaded Convolutional Neural Network Segnet achieve 0.8 F1-score.

(Bah et al., 2018) has used unsupervised approach for weeds detection on unmanned aerial vehicle (UAV) base on novel fully automatic learning method using Convolutional Neuronal Networks (CNNs).

(Lottes et al., 2018) has use Joint Stem Detection approach for Crop-Weed Classification for Plant-specific Treatment in Precision Farming gives improvement in the semantic segmentation performance. using CNN encoder and decoder Architecture.

(Fawakherji et al., 2019) has shown pixel wise segmentation for crop and weed using VGG-UNet,VGG-Segnet and UNet deep learning architecture.

(Haug et al., 2014) use a Random Forest classifier to estimate crop / weed certainty at sparse pixel positions based on features extracted from a large overlapping neighbourhood achieve 93.8 accuracy

(Lottes et al., 2016) has thoroughly evaluated our system using a real farm robot in different sugar
beet fields, and we illustrate that our approach allows for accurately identifying weeds in a field.

(Teimouri et al., 2018) has outlines a new method of automatically estimating weed species and growth stages using deep convolutional neural networks Inception-v3 has a relatively high ability to estimate early growth stages across a wide variety of weed species.

(Chebrolu et al., 2017) has create dataset for weed detection in sugar beet which is publicly available for researchers.

(Haug et al., 2015) has create dataset for weed detection in organic carrot farm which is publicly available for researchers.

Precise weed detection in precision agriculture we found that publicly available dataset and recently launch challenge on colalab they also providing dataset with this open dataset we will implement crop, weed and soil segmentation deep learning based model try to beat existing papers.

Summary of the deep learning for solving precision agriculture tasks such as plant diseases detection, weed detection with the number of papers and example sources Since 2014.

Precision agriculture tasks	No. of Papers	Source (example)
Plant diseases detection	22	Chen et al. 2014, Zhang et al. 2016, Long et al. 2017, Pei et al. 2018
Plant species identification	6	Wang et al. 2015, Panboonyuen et al. 2017, Wei et al. 2017
Weed detection	4	(Masi et al. 2016, Wei, Yuan, et al. 2017, Wang et al. 2018)
Semantic segmentation	49	Paisitkriangkrai et al. 2016, Maggiori et al. 2017, Wu et al. 2018
Land cover image classification	8	Kussul et al. 2017, Pan and Zhao 2017, Zhang et al. 2018
Land use scene classification	72	Hu et al. 2015, Othman et al. 2016, Nogueira et al. 2017, Liu et al. 2018
Change detection	5	Zhang et al. 2016, Gong et al. 2017, Su et al. 2017

From the table there are seven types of major applications. the remote sensing domain: target detection, road extraction, image processing, semantic segmentation, land cover image classification, land use scene classification and change detection. Among the seven applications, the land use scene classification (72 papers), semantic segmentation (49 papers) and target detection (22 papers) constitute the majority cases, whereas others are less researched so far Instead, the purpose is to provide a concise overview of deep learning methods for LC and LU application using remotely sensed imagery. We focus on deep convolutional neural networks (CNN), as they are the most typical and well-established deep learning method that has been adopted in the remote sensing domain.

4. Research Objectives

The main objective of this research is to produce the deep learning-based Plant diseases detection and diagnosis system will approach towards smartphone-assisted crop diseases diagnosis system and weed detection system which will increase crop yield and reduce environmental loss because of herbicide. To reach this aim, the following specific objectives are,

- Create pigeon pea plant leaf image dataset with help of agriculture experts which will be publicly available for researchers.

- Undertake a brief study on deep convolutional neural network techniques for plant diseases detection using plant leaf images.

- Develop a deep learning method that will detect Plant diseases in pigeon pea plant leaf image.

- Design weed detection system will detect and classify weeds in images from fields. This is the first step of an automated precision weed control system.

- Develop a deep learning method that will predict yield using remotely sensed/UAV images.

5. Methodology to be adopted

Deep learning: Deep Learning is a machine learning technique that learns features directly from the data. The data can be image, text, speech or audio. Most deep learning methods used neural network architecture. Hence deep models refer to a deep neural network. The term ’deep’ in deep neural networks refers to the number of hidden layers present in the neural network. One popular neural network model is a convolutional neural network (CNN). Convolutional neural networks are best suited for image data. Basically, we can classify learning techniques into two categories.

1. Supervised learning.
2. Unsupervised learning

1.2.1 Supervised learning

If we are training a specific machine learning task for every input with corresponding target values or labels, then it is called supervised learning. Supervised learning methods will try to learn the relation between the input and its target label. Supervised learning can be of regression or classification. If he target represents continuous values, then it is a regression problem. If the target is represented with finite number of classes, then it is a classification problem.

1.2.2 Unsupervised learning

If we are training a specific machine learning task with only input data then it is unsupervised problem. Unsupervised learning methods try to learn the structure of the data or the relationship among the data points. Clustering is one of the unsupervised methods which tries to divide the data
into different clusters. So for a new test data, it will match to the appropriate cluster.

6. Evaluation

Confusion matrix

The confusion matrix is used to describe the performance of a classification model on a set of test data for which true values are known.

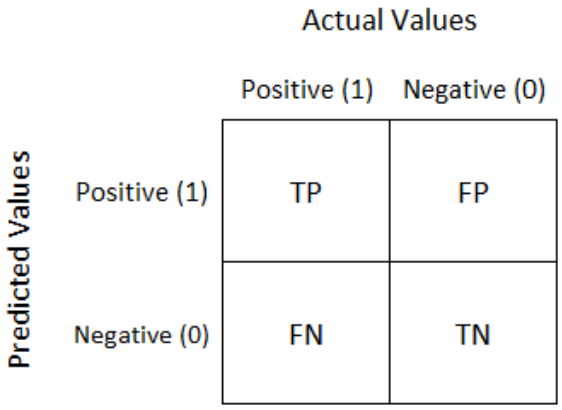

Figure (1). Confusion Matrix

From the confusion matrix the following information can be extracted:

True positive (TP): This shows that a model correctly predicted Positive cases as Positive. Example. an illness is diagnosed as present and truly is present.

False positive (FP): This shows that a model incorrectly predicted Negative cases as Positive. Example. an illness is diagnosed as present and but is absent.

False Negative (FN): This shows that an incorrectly model predicted Positive cases as Negative. Example. an illness is diagnosed as absent and but is present.

True Negative (TN): This shows that a model correctly predicted Negative cases as Positive. Example. an illness is diagnosed as absent and truly is absent.

Precision score: This is the measure of the accuracy, provided that a class label has been predicted. Simply put, it answers the following question, of all the classes, how many were correctly predicted? The answer to this question should be as high as possible.

$$Precision = \frac{TP}{TP + FP}$$

Recall score(Sensitivity): This is the true positive rate that is if it predicts positive then how often does this take place?

$$Recall = \frac{TP}{TP + FN}$$

F1 score: Calculated based on the precision and recall of each class. It is the weighted average of the Precision and the recall scores. The F1 score reaches its perfect value at one and worst at 0. It is a very good way to show that a classifies has a good recall and precision values.
We can calculate it using this formula:

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

Intersection Over Union (IOU): These are defined as follows: IOU is interpreted as the name suggests: the intersection of the actual and predicted values, divided by the union of this set for a specific class.

$$IoU = \frac{TP}{TP + FP + FN}$$

7. Conclusion

Thus, from literature for plant diseases detection lack of availability of dataset so we will
Create pigeon pea dataset with agriculture experts and develop deep learning based method for plant diseases detection will also develop deep learning based method for weed detection to achieve precision agriculture i.e crop yield should increase and should reduce environmental damage impact because of herbicide.

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